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The Artificial Neural Networks to obtain port planning parameters

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Abstract

Artificial Neural Networks can be a great help in port planning activity. Bad planning might lead to an incorrect use of the available resources and means.
This research is focused on neural networks' behavior analysis within the port planning process, in the context of containers terminals, more precisely to study the possible traffic growth and the requirements in terms of equipment and installations. The traffic levels in these terminals and the minimum necessary investment can be thus evaluated with no need or with just a very low new investment.
The methodology shows the fundamentals of the Artificial Neural Networks application and the considered sequence to develop the container port terminals planning, supported by the MATLAB code tools.
The article reaches finally the conclusion that both the tool and the proposed methodology can be considered as acceptable to perform this kind of planning forecasts and to be used in the future.
The results seem to show that the ANN can be used to model port planning issues linked to container terminals, based on historical data series.

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Keywords: Containerized traffic (trade), artificial neural networks, planning, forecast

1. Introduction

Since the origin of the world crisis back in 2008, the investments have generally shown a dramatic decrease, and this situation has been also noticed in port terminals extensions. Developed countries, i.e. Japan, United States, Hong Kong, Canada, Spain, Singapore or Chile, had to face a stronger effect, although emerging countries like Mexico or

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China have also been influenced. The high prices of raw materials, particularly the crude, the food, the metals, the copper, influenced the decrease of the sea traffic and thus the container operations.

One of the main problems in port logistics, as well as in other fields of freight transportation engineering, is to forecast the parameters characterizing the needs in space, resources and means, and their optimization. Physical and equipment parameters of a container terminal (stocking surface, necessary berthing length, number of dock cranes…) represent a huge investment and strong environmental and socio-economical impacts.

Therefore, the need of a correct forecast of these parameters and thus of the real surface needs (to minimize the environmental impact), make of this research a very useful tool for the planning agent, ensuring a reliable prediction in terms of space and means, and correct marketing, strategic and planning decision making processes.

The fact is even more important during this stage of economical crisis, when any investment or environmental intervention has to be analyzed from a strictly practical point of view and focused on the bare necessity, in order to not turn into an unnecessary growth instrument.

Having defined the problem, the research team in the Polytechnic University of Madrid decided to investigate the approach for using the ANN in port planning, precisely in singular container terminals all over the world. The research continues the works already carried out by the authors of this article.

Up to these days, the port planning process was basically based on empirical methods (Rodríguez, 1977; BTRE, 2006; Drewry, 1998, Drewry, 2005, Fourgeaud, 2000; Rodríguez, 1985; Schreuder, 2005 and Soler, 1979), analytical methods (Rodríguez, 1985; UNCTAD, 1984, Agerschou, 2004, Dragovic, Zrnić & Radmilović, 2006) or simulation methods (UNCTAD, 1969 and UNCTAD, 1984). Many port planning studies have been developed over the years, although none of them dealt with a possible crisis scenario, or with a forecast method using artificial neural networks.

In Spain, the first references are in 1977. (Rodríguez, 1977) analyze basic issues of the port planning. Later on, (Soler, 1979) publishes a comparison between the operation condition in several Spanish ports using empirical methods. More recently, another article (Camarero & González, 2009), group the parameters to be taken into account in the container terminal planning. In 2007 (González, 2007), determines in a Ph.D. work the parameters and the characteristic ratios of the port operation, obtaining values to be used in the case of container terminals. Other publications that can be cited here (Quijada-Alarcón, González, Camarero & Soler, 2012) deal with the logistic planning.

A significant improvement in port planning can be reached using artificial intelligence, precisely the artificial neural networks. However, the references are rather poor, mainly due to the recent applications of the artificial intelligence in our society. The first publications were issued back in 1943 (Warren & Walter, 1990) somehow difficult in the making, and with a very poor approval of the research community. New interest for these techniques was generated in 1982, when (Hopfield, 1982) establishes the Backpropagation algorithm.

The artificial neural networks' application to transportation issues are focused on: Driver's Behavior, Parameters Estimation, Pavement Maintenance, Vehicles' Detection and Classification, Traffic Patterns Analysis, Loading Operations, Traffic Forecasts, Transportation Politics and Economy, almost all of them linked to linear traffic (highways and railways) or air traffic. The artificial neural networks applications to sea transport and furthermore to port planning are practically inexistent (Rodríguez, González & Soler, 2013).

The most significant studies that can be subscribed to this article have been carried out by (Clark, Dougherty & Kirby, 1993; Dougherty, Kirby & Boyle, 1994 and Dougherty, 1995; Vlahogianni, Karlaftis & Golias, 2005; Tsai, Lee & Wei, 2009; Gosasang, Chandraprakaikul & Kiattisin, 2010; Moscoso, Ruiz & Cerbán, 2011; Gosasang, Chandraprakaikul & Kiattisin, 2011; Karlatis & Vlahogianni, 2011).

Using the artificial intelligence, this article describes a research that aims to obtain useful results to be used in the decision making process and in means and resources optimization, to reinforce the society's welfare.

The analysis is carried out through a multiple comparison scheme, randomly generated using the NNtex tool, based on the Artificial Neural Networks.

2. Methodology

The developed methodology allows future traffics determination of the container terminals, assuming that no investment is planned, i.e. without modifying the physical parameters (berthing, surface, dock cranes,...). On the other hand, it also allows the physical parameters future needs evaluation taking into account the growth forecast.

The analysis is carried out through a multiple comparison scheme, randomly generated using the NNtex tool (Li, Orive, Flores & Cancelas, 2013), based on the Artificial Neural Networks.

The Artificial Neural Networks (ANN) are inspired by the human brain's biological neural networks. The main characteristics reproduced by the artificial neural networks can be reduced to the following three concepts: parallel processing, carried out by artificial neurons, distribution by a layers complex, and adaptation through learning from experience and minimizing the error (Martín del Brío & Sanz, 2002).

The artificial neural network model is composed by a number of inputs ($x_j(t)$); synaptic weights (w_{ij}) representing the communication degree between neurons j and i; a propagation rule $\sigma_i(w_{ij}, x_j(t))$ which determines the interaction potential between neuron i and the N neighbouring neurons; an activation function $f_i[a_i(t-1), h_i(t)]$ associated to the neuron i, determining the neuron's activation state, based on the resultant potential h_i and the neuron's previous activation state $a_i(t-1)$; and an exit function ($F_i(a_i(t))$ representing the answer of the neuron i, given by the following formula(1):

$$Y_i(t) = F_i(f_i(a_i(t-1), \sigma_i(w_{ij}, x_j(t)))) \tag{1}$$

Thus, the learning process of a neural network can be seen as the adjustment process of the network's free parameters. Starting from a random synaptic weights set of values, the learning process searches a set of values that would allow the network to correctly develop a specific task. The learning process is therefore an iterative sequence that will refine the solution until a sufficiently good operation level is reached.

2.1. Phases:

The following phases have been developed in the methodology:

2.1.1. Phase I: Data acquisition, classification and discretisation of the values obtained from the terminals.

This first phase performs a diagnosis of the containers terminals actual state within a wide variety of geographical conditions; data to be processed are also acquired, classified and arranged. (Table 1).

Dealing with a neural network, the number of variables to be considered can be practically infinite. Databases sizes can be considerable, as well as the fields' number.

Terminals values are processed during the correspondent number of years.

Databases can be generated during the process, to relation different variables like number of berthing points, stocking capacity, crane time, waiting time, berthing number and time, dock length, terminal surface, total cranes number or equipments to be used, optimum stocking areas occupation, operated containers quantity, terminal and its subsystems capacities, etc.

Table 1. Data processing example.

Date	Cod_port	Cod_country	Long_berth	Term_surface	Cranes	TEU
2003	1	1	1.610,00	48,50	9,00	639.570,00
2003	2	2	3.803,00	158,33	46,00	1.539.058,00
2003	3	3	1.230,00	1,50	14,00	47.266,00
2003	4	3	3.143,00	5,38	2,00	135.267,00
2003	5	3	1.155,00	37,14	10,00	524.376,00
2003	6	3	2.611,00	23,54	14,00	319.368,00
2003	7	4	3.367,00	113,60	48,00	1.332.746,00
2003	8	4	2.281,00	82,50	64,00	11.280.000,00
2003	9	4	1.110,00	71,50	27,00	2.331.000,00
2003	10	4	2.450,00	100,44	20,00	3.015.000,00
2003	11	4	2.350,00	118,00	30,00	5.258.106,00
2003	12	5	11.040,00	301,33	120,00	10.407.809,00
2003	13	5	700,00	42,00	14,00	1.184.842,00
2003	14	6	1.515,00	23,50	5,00	468.599,00
2003	15	7	270,00	4,90	3,00	65.576,00
2003	16	8	400,00	47,80	3,00	174.108,00
2003	17	9	5.754,00	217,00	67,00	13.100.000,00
2003	18	9	3.000,00	65,00	30,00	5.919.000,00
2003	19	10	5.440,00	173,36	88,00	2.504.627,00
2003	20	11	486,00	70,00	4,00	44.836,00
2003	21	11	286,00	18,50	6,00	1.646,00
2003	22	11	2.205,00	30,80	24,00	709.209,00

2.1.2. Phase II: Building the artificial neural network.

The artificial neural network is built using the Matlab application, creating a multilayer perceptron network through a learning algorithm backpropagation with adaptable learning speed (Fig. 1).

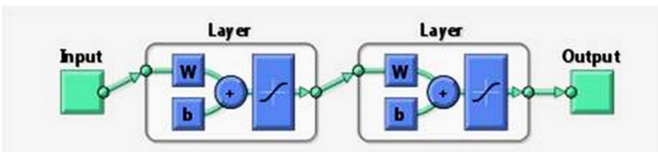

Fig. 1. Network architecture scheme

Training method is a momentum descending gradient. Once created, and alter an initial simulation process, the network is trained using known inputs and outputs, representing real container terminal data, aiming that the network adjusts its outputs through modifying the weights and threshold values, in order to minimize the errors.

2.1.3. Phase III: Network functioning and obtained results analysis.

Before any process, the training percentage to be considered has to be defined. This comes to show what part of the data will be used for training and what part for the test, in order to verify model's effectiveness.

The number of epochs, in other words, the number of times real data have been compared to model's outputs to perform connections' weights adjustments.

The following variables, obtained from the neural network training process, will be used to analyse network's functioning:

- Correlation coefficient (C), that allows the comparison between two different observations of the same or different variables that quantifies the relation degree between real data and network's forecast. This variable (2) can be written as:

$$C = \frac{\sum_{i=1}^{N}(O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{N}(O_i - \overline{O})^2 \sum_{i=1}^{N}(P_i - \overline{P})^2}} \tag{2}$$

were;

O_i, is the real value; P_i, is the forecasted value; N, is the number of data

- Average squared error (MSE), that measures system's error (3), and can be defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(O_i - \overline{P_i})^2 \tag{3}$$

During the training phase (Fig. 2), output variables or real values are compared to the forecasted ones.

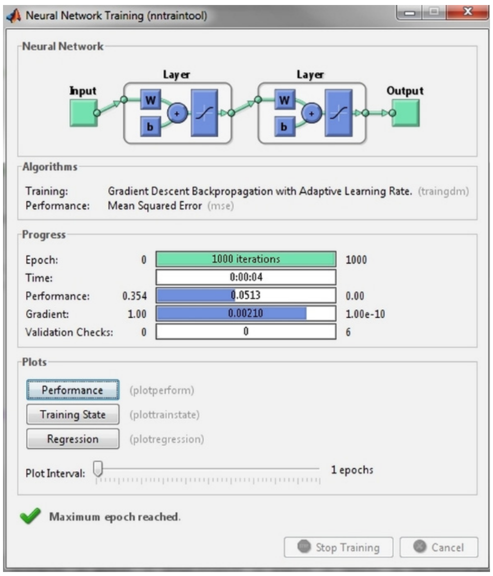

Fig. 2. Network's training module image

This process allows the estimation of network's approach based on training data, as shown by the graph below (Fig. 3).

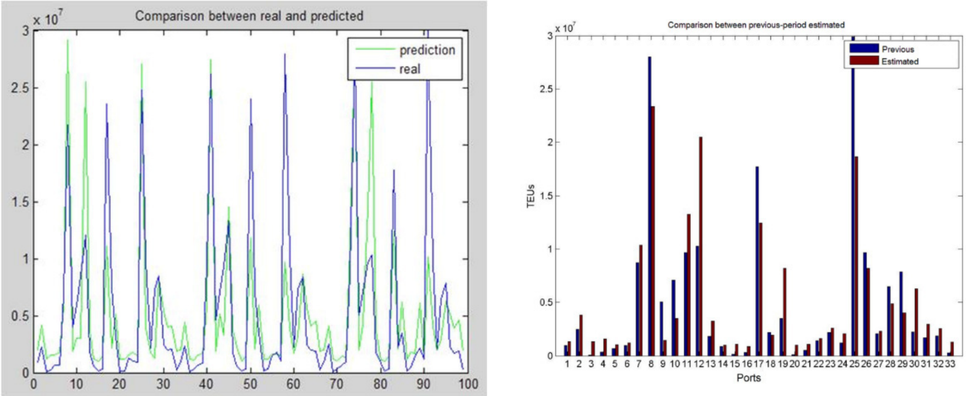

Fig. 3. Approach comparison between real and forecasted values

2.1.4. Phase IV: Neural network validation.

Once verified that network's outputs after the training process, are within the accepted range of parameters values (Correlation coefficient, Average squared error, etc).

At this process, the network can be validated, estimating its suitability for a real case application

2.1.5. Phase V: Scope of the study.

In the last phase, once validated the neural network, a detailed study of the various container terminals is done by evaluating the state are based on facilities, equipment and estimates of current traffic in these terminals and their forecasts future.

3. Results

The results allows us to verify the possibility of artificial neural networks to port planning, comparing real data with the forecast and future needs in terms of surface, equipment and means.

Following the previously described sequence, the study has been carried out as detailed below.

Data and traffics of 33 ports between 2003 and 2011 have been collected and analyzed (Table 2). Subsequently, these data have been structured by assigning them to the different fields of the network. The fields contain data as the date, container terminal name, country, dock length, terminal's surface, number of dock cranes or the operated container number.

The analyzed and structured port data allowed to build the neural network structure. Network's algorithms are the ones showed in Fig. 4.

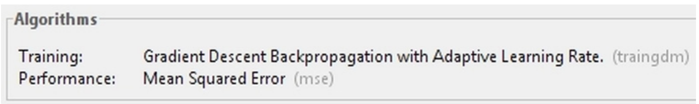

Fig. 4. Network algorithms considered

Table 2. Ports analyzed with ANN.

Reference	Name	Country

Reference	Name	Country
1	Brisbane	Australia
2	Vancouver	Canada
3	Antofagasta	Chile
4	Iquique	Chile
5	San Antonio	Chile
6	Valparaiso	Chile
7	Qingdao	China
8	Shanghai Total	China
9	Xiamen	China
10	Tianjin	China
11	Yantian	China
12	Bussan	Korea
13	Kwangyang	Korea
14	Guayaquil	Ecuador
15	Acajutla	El Salvador
16	Puerto Quetzal	Guatemala
17	Hong Kong KCTY	Hong Kong
18	Hong Kong RTT	Hong Kong
19	Yokohama	Japan
20	Ensenada	Mexico
21	Lazaro Cardenas	Mexico
22	Manzanillo	Mexico
23	Balboa	Panama
24	Callao	Peru
25	Singapore	Singapore
26	Kaohsiung	Taiwan
27	Keelung	Taiwan
28	Long Beach	USA
29	Los Angeles	USA
30	Oakland	USA
31	Seattle	USA
32	Tacoma	USA
33	Portland	USA

Network’s parameters are as follows (Table 3):

Table 3. Network's parameters.

Input layers	Hidden layers	Output layers	Epoch	Learning rate	Momentum
3	5	1	1000	0,3	0,6

Different analysis have been performed within the study. Some of them are briefly cited below.

3.1. Network's behavior analysis for traffic growth assumptions

Through parameters such dock length, terminal's surface and dock cranes number a network's behavior analysis is performed in order to estimate the future traffics. This showed estimations very close to the observed values as shown in Fig. 5.

The mean square deviation MSE adjustments and the different correlation comparisons show an approximation of more than 80% and never less tan 70%.

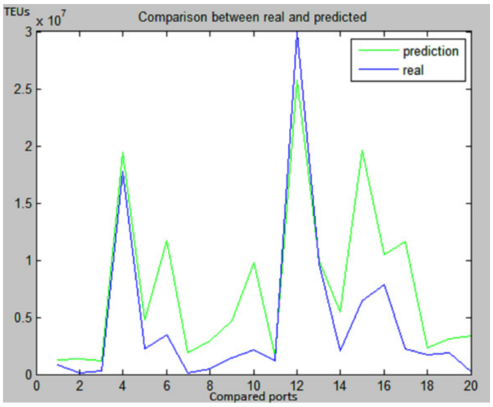

Fig. 5. Graph for %(T-T) 90-10 and 3000 iterations

3.2. Network's behavior analysis for traffic growth assumption and collapse state due to new conditions

The neural network used as initial variables the dock length, terminal's surface and dock cranes number, and estimating the operated container number, TEU's. The results obtained assuming that no investment is realized, seem to lead to the conclusion that investments should be directed to Asian and North American countries, based on registered last years' traffic increase in the considered terminals. Fig. 6, shows some results of the study.

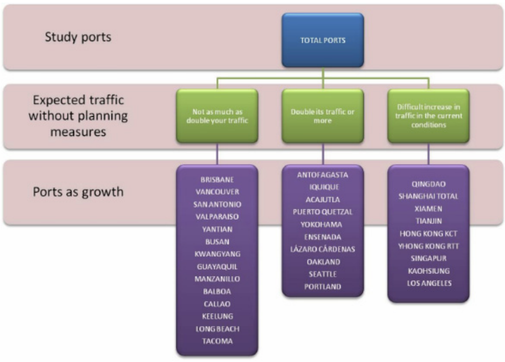

Fig. 6. Key findings of the research. Case Example

4. Conclusions

Artificial intelligence, precisely the artificial neural networks applied to the port planning activity, may lead to its significant improvement. Very poor references can be cited though, due mainly to the early age of the artificial intelligence.

Detailed research programs on the artificial neural networks are nowadays developed by many universities worldwide (Boston, Helsinki, Stanford, Carnegie-Mellon, California, Massachusetts), together with some private companies based in Japan, United States and Europe – Spain among them.

Examining the results obtained by the research described above, one could state that the artificial neural networks can be successfully used in port planning modeling, related to container terminals, based on historical data series.

The needs in equipment and surface can be estimated based on TEU's forecasts or vice versa and can be successfully used in container terminal planning.

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